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Optimizing Steam to Electricity Ratio in Crude Palm Oil Refinery Captive Power Plant: A Six Sigma-DMAIC Capability Assessment

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ABSTRACT

This study applies the Six Sigma-DMAIC (Define, Measure, Analyze, Improve, Control) methodology combined with process capability analysis to enhance energy efficiency, specifically by reducing the steam to electricity ratio of a steam turbine. Initial measurements indicated a steam-to-electricity ratio of 4.5 to 5.34 kg/kWh, highlighting high steam consumption and poor efficiency. The process was unstable, with Cp and Cpk values of 0.30 and -0.16, and a defect rate exceeding 560,000 DPMO. Using an Ishikawa diagram, a vacuum leak in the steam turbine condenser was identified as the main cause of excessive steam consumption. After repairing the condenser, monitoring showed significant improvements, with the steam to electricity ratio reducing to 3.0 – 4.0 kg/kWh. Process capability improved, with Cp increasing to 1.39, Cpk to 1.02, and Z-bench to 3.05 (equivalent to 1,143 DPMO). The Anderson-Darling test confirmed a normal distribution (p-value = 0.464). Six Sigma-DMAIC effectively optimized steam turbine performance.

KEYWORDS: *Six sigma, DMAIC, process capability, steam turbine, energy efficiency, C_p, C_{pk}, Z-bench, Anderson-Darling.*

NOMENCLATURE

C_p	*Process Capability Index*
C_{pk}	*Process Capability Index - Centered*
PCR	*Capability Ratio*
USL	*Upper Specification Limit*
LSL	*Lower Specification Limit*
DPMO	*Defects per million opportunities*
μ	Process mean
σ	Standard deviation
m	Mid-point
n	Number of Sample
AD	Anderson-Darling
P	Probabilities
PDF	probability density function

1.0 INTRODUCTION

In the Crude Palm Oil (CPO) manufacturing process, steam plays an important role as the main energy source supporting plant operation, both in the production plant as heat exchanger and in the power plant for electricity generation. It is crucial for ensuring and reducing production operational cost[1], [2], [3]. PT. XYZ is one of the CPO manufacturing companies (RBDPO Olein and Stearin product) located in Dumai City, Riau Province, Indonesia, which has its own electricity generation system to support plant operations. Out of the three main power plant machinery options (Diesel Generator, PLN-supplied electricity, and Steam Turbine) the management of PT. XYZ has selected the steam turbine and biomass boiler as the primary units to support operational activities.

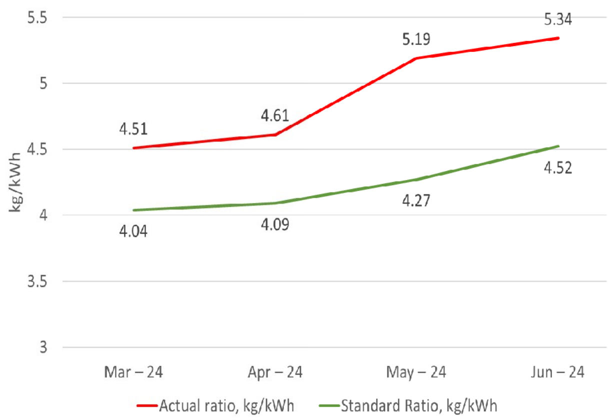

Figure 1: Actual and standard steam-to-electricity ratio

The Figure 1 illustrates the comparison between the actual steam-to-electricity ratio and the standard ratio from March to June 2024 in PT XYZ. Throughout the observed period, the actual ratio consistently remained above the standard, indicating inefficiencies in steam utilization for power generation. In March 2024, the actual ratio was 4.51 kg/kWh, slightly higher than the standard of 4.04 kg/kWh, and this gap widened in the subsequent months.

By June 2024, the actual ratio reached 5.34 kg/kWh, while the standard ratio was 4.52 kg/kWh, showing a continuous upward trend and growing deviation. This suggests that the turbine and steam distribution systems were operating below optimal efficiency, leading to increased steam consumption per unit of electricity generated. The data highlights the need for performance improvement and process optimization to align actual performance with standard expectations. Standard ratio shown based on data from manufacturer of steam turbine.

Figure 2 shows the steam process originating from the boiler. The high-pressure steam is generated and subsequently directed to the steam turbine.

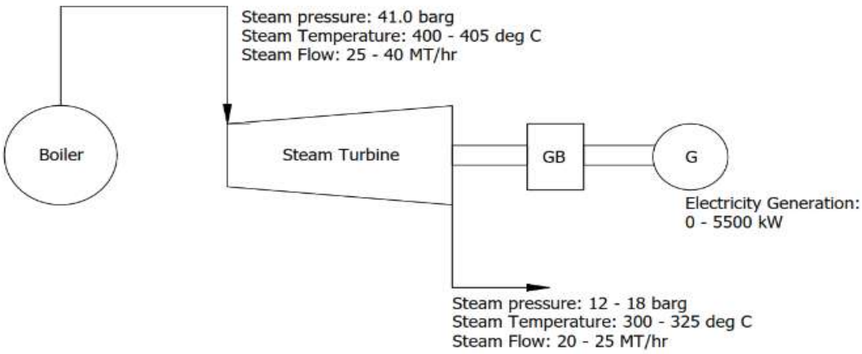

Figure 2: Steam turbine process at PT. XYZ

This study investigates the integration of the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) methodology with process capability analysis as a strategic approach to enhance energy efficiency in a crude palm oil (CPO) manufacturing facility equipped with an in-house power generation system. The research primarily focuses and aims on optimizing the performance of the steam turbine by reducing the steam-to-electricity ratio, thereby contributing to improved operational efficiency and reduced energy consumption.

Therefore, the Six Sigma DMAIC approach in this study is necessary to address specific operational challenges identified in the power generation process at a palm oil mill (CPO). For example, a sub-optimal steam-to-electricity ratio indicates inefficiencies in steam utilization for electricity production. This challenge indicates significant issues in the efficiency of the power generation process, requiring a systematic approach such as Six Sigma DMAIC to identify and eliminate the causes of variation and defects.

2.0 THEORITICAL BACKGROUND

2.1 Literature Review

Kaushik and Khanduja [4] applied the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) methodology in a thermal power plant to reduce demineralized (DM) water consumption and enhance customer satisfaction through continuous process improvement. The implementation was supported by various analytical tools, including a High-Level Process Map, SIPOC diagram, Gauge R&R, process capability analysis, run chart, histogram, and fishbone diagram. As a result, DM water consumption decreased from 0.90% to 0.54% relative to Maximum Continuous Rating (MCR), leading to an estimated annual cost savings of approximately USD 33,327.93. The initiative also achieved a defect reduction of over 95% and significantly improved process efficiency

Sudhakar et al. [5] in his research, implemented the Six Sigma DMAIC (Define, Measure, Analyze, Improve, Control) methodology to improve performance in a thermal power plant by reducing leakage and variability in demineralized (DM) water consumption, thereby lowering operational costs. Using data from the power plant and statistical analysis via Minitab 17.1, the study employed tools such as capability analysis and before/after comparison. The results showed a significant reduction in DM water consumption, with the process average moving closer to the target and the standard deviation decreasing by half. Process capability improved notably, with Pp increasing from 0.53 to 1.00 and Ppk from 0.47 to 0.92. Defect rates dropped from 5.47% (54,680 PPM) to 0.36% (1,363 PPM), leading to an estimated annual cost savings of approximately USD 120,000.

Kumar [6] used Six Sigma DMAIC approach to identify the main causes of low availability of the steam and power generating system. The revealing of the economizer, re-heater, and super heater are the main causes of variation for failure or low availability of the system. The failure contributes to increased operational costs.

Thamir K and M.M [7] conducted a study to evaluate the effects of isentropic efficiency in compressors and turbines on the performance of various gas turbine configurations. Using a MATLAB-based computational model, they performed a parametric analysis across five configurations: Simple Gas Turbine (SGT), Two-shaft Gas Turbine (TGT), Intercooled Gas Turbine (IGT), Regenerative Gas Turbine (RGT), and Reheat Gas Turbine (HGT). The results demonstrated that isentropic efficiency significantly influences both power

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output and thermal efficiency. Among the configurations, HGT (Reheat) produced the highest power output at 268 MW, while RGT (Regenerative) achieved the highest thermal efficiency at 50.8%. In contrast, SGT recorded the lowest thermal efficiency at 39.5%. The study also noted that the maximum achievable thermal efficiency across all configurations was 52.4%.

Alshaiba [8] investigates techniques to reduce energy consumption in 132 KV substations in Dubai, particularly by optimizing HVAC system functioning and design, and proposes solutions such as regular inspections, airflow meters, and data analysis tools. The study uses the DMAIC Lean Six Sigma method, which involves defining, measuring, analyzing, improving, and controlling processes. The study also uses statistical tools such as the fishbone diagram and the 5 WHY's tool to identify root causes of high-power consumption. Additionally, the study uses statistical sampling to select a representative sample of substations. The methods used in the study include detailed energy audits, analysis of HVAC system design and operation, and proposal of solutions such as regular inspections, airflow meters, and data analysis tools. The results of the study show that implementing the proposed solutions can reduce power consumption by 10%. The study also found that the total cost savings generated from implementing the solutions is AED 2,198,753.33 (USD 598,568.82) per year.

2.2 Six Sigma and DMAIC

Six sigma is a performance improvement approach that seeks to find and eliminate causes of defects and errors, reduce cycle times and cost operation, improve productivity, better meet customer expectation, and achieve higher asset utilization and returns on investment in manufacturing and service process [9]. As a core component of Six Sigma, the DMAIC (define, measure, analysis, improve and control) methodology relies on quantitative data analysis to systematically identify and eliminate sources of variation and defects a process [10], [11].

DPMO (defects per million opportunities) is used to determine standard a way of measuring quality for any process of six sigma [9], [12] which defined as follow:

$$DPMO = \frac{Number\ of\ defects}{Opportunities\ of\ error} \times 1{,}000{,}000 \qquad (1)$$

The sigma level can be determined using the following excel formula [9]:

$$\sigma\ level = NORM.S.INV\left(1 - \frac{dpmo}{1000000}\right) + 1.5 \qquad (2)$$

The corresponding Sigma levels are shown in following table 1.[12].

Table 1:Percent output acceptable from the process and the corresponding Sigma level [12]

Percent acceptable	DPMO	Sigma level
30.9	690000.0	1
62.9	308000.0	2
93.3	66800.0	3
99.4	6210.0	4
99.98	320.0	5
99.9997	3.4	6

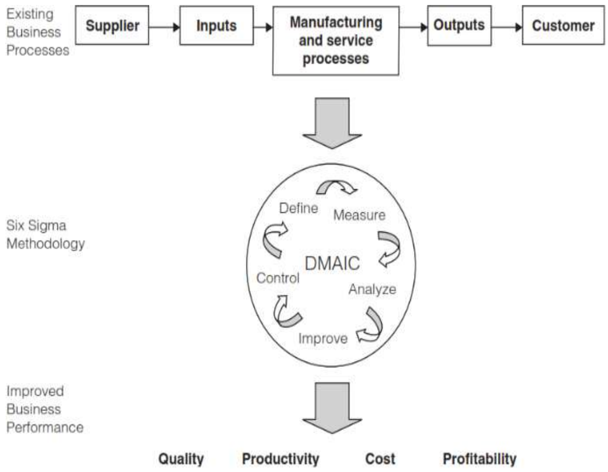

Figure 3: Six sigma and process improvement [9]

The DMAIC problem-solving approach consists of five fundamental phases: Define, Measure, Analyze, Improve, and Control [13]. Figure 3 explain DMAIC methodology and process tools. The initial phase of the DMAIC methodology (define) involves a comprehensive definition of the problem statement.

In measure phase data should be served measurably, as quality and safety are identified. Data extracted from aggregate databases should be analyzed for accuracy [14].Analyze step merges what is known about the process as well as the baseline data to identify and validate the causes of errors, deviation, delays, waste, or other etiologies of defects in the process. Analysis may include pareto diagrams, histograms, pie charts, Ishikawa (fishbone) diagrams, a 5-whys analysis, or other tools to explore cause and effect [15].In improve step, the team focuses on identifying and eliminating the root causes of problems, implementing changes to reduce variability and eliminate waste in the process. The kaizen philosophy, which translates form Japanese as ”change for better,” reinforces the idea that operational improvements should be a collective effort involving all employees and should follow a continuous and systematic approach [14].

Last step is controlling phase. The control phase is essential for maintaining long-term improvements and involves monitoring process performance through a detailed control plan that outlines responsibilities for each part of the updated process. The team must stay alert to potential issues such as workarounds, design weaknesses, or resistance to changes, while using control charts to track variations [14]. Regular awareness of performance metrics is necessary to address deviations promptly, with the frequency of updates depending on the type of metric and the time needed to collect and validate the data.

2.3 Capability Assessment Analysis

Assessing process capability plays a vital role in quantitative quality control, where process capability indices (PCIs) serve as statistical tools to evaluate how well a process performs [16], [17]. Process capability analysis as a formal study to estimate process capability. The estimate of process capability may be in the form of a probability distribution having a specified shape, center (mean), and spread (standard

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deviation)[16]. Process Capability Ratio (PCR), C_p, which for a quality characteristic with both upper and lower specification limits (USL and LSL, respectively) is [17]:

$$C_p = \frac{USL - LSL}{6\sigma} = \frac{d}{3\sigma} \tag{3}$$

where USL and LSL are the upper and lower specification limits, respectively d refers to half of the length of the specification interval, and σ denotes the process standard deviation for an in-control process [17]. Since the $C_p$does not account for process mean (μ), any deviation of mean (μ) from center of specification range is ignored in its calculation. As a result, two processes with identical standard of deviation (σ), but differing means (μ) will yield the same $C_p$value. Nevertheless, a greater shift in the process mean increase the likelihood that the process output will fall outside the specification limits, leading to a less accurate representation of actual process capability.

Consequently, Kane[18], proposed another process capability index, C_{pk}, which is defined as follows:

$$C_{pk} = Min\left\{\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\} = \frac{d - |\mu - T|}{3\sigma} \tag{4}$$

where $T = (USL + LSL)/2$ denotes target value and $d = (USL - LSL)/2$. Thus, the C_{pk} index relates the scaled distance between the process mean and the closest specification limit.

Denote the midpoint of specification range by [18]:

$$m = \left(\frac{USL + LSL}{2}\right) \tag{5}$$

In process performance indexes, P_p, and P_{ck}, mathematically, these are exactly the same as process capability indexes *and* C_p, and C_{pk} [9].However, this approach reflects the actual, rather than the ideal, performance of a process operating in an uncontrolled environment, which may be affected by special causes of variation. In practice, this is considered questionable, as many experts advise against it. Controlling the process and eliminating special causes of variation is essential for achieving high quality and ensuring customer satisfaction. In table 2 shown the Recommended Minimum Values of the Process Capability Ratio

Table 2: Recommended Minimum Values of the Process Capability Ratio [9]

	Two-sided specification	One-sided specification
Existing Process.	1.33	1.25
New Process.	1.50	1.45
Safety, strength, or critical parameter, existing process.	1.50	1.45
Safety, strength, or critical parameter, new process.	1.67	1.60

Every statistical test relies on specific assumptions, and if these assumptions are not met, the analysis can produce inaccurate conclusions and untrustworthy outcomes [19], [20], [21]. Various tests, commonly referred to as goodness-of-fit tests, are employed to determine whether a set of observed data can be regarded as originating from a specific probability distribution. One of frequently used goodness-of-fit test is Anderson-Darling (AD). The procedure of AD is how close the points are to the straight line estimated in a probability graphic. On the ordered probabilities (on P), several statistics can be computed, and Anderson–Darling (AD) is one of them [19]:

$$AD = AD(P,n) = -n - \sum_{i=1}^{n} \frac{(2i-1)\ln(p_i(1-p_{n-i+1}))}{n} \tag{6}$$

Where the series P = (p_1, p_2, . . . , p_n) defined by p_i = InvCDF(x_i). Let the CDF be the associated cumulative distribution function and InvCDF the inverse of this function for any PDF (probability density function)[19].

3.0 METHODS

3.1 Data Collection Procedure

The data used in this study were obtained from the daily operational records of the steam turbine in the house power generation system of PT. XYZ. The data collection period was divided into two main phases:

- *Before Improvement (Baseline Phase)*

The period for data collection before improvement is February 1st, 2024 to June 26th, 2024. Data were recorded daily at end of shift (7:00 PM WIB). The recorded parameters are steam produced by boiler, steam consumed by each plant (refinery, fractionation, fatty acid plant, oleo plant, deaerator, tank farm and turbine). Steam produced and steam consumption should be balance. The instruments used were a steam flow dan kWh meter provided by the manufacturer. There are several days with missing data, indicating that the turbine or plant was not in operation during those periods.

- *After improvement (post improvement monitoring)*

Following the implementation of improvements, the post-improvement monitoring phase took place from June 27th, 2024 to June 25th, 2025. Data were collected the same frequency, parameters, and instruments as in the baseline phase. However, several days had missing data due to turbine shutdowns, during which electricity supply was temporarily sourced from PLN (Perusahaan Listrik Negara). The research was carried out across both the pre-improvement and post-improvement phases.

To ensure data reliability, steam flow meter and kWh meter were calibrated annually by electrical and instrument team. Data collection was carried out by the utility team and documented digitally using a centralized monitoring system (SCADA). As shown in Figure 4.

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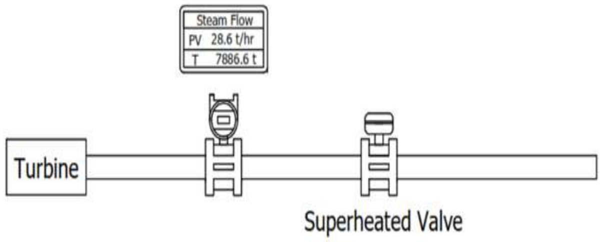

Figure 4: Scada steam flow to Turbine

3.2 DMAIC, Six Sigma, And Process Capability Assesment Method

This research was carried out using DMAIC, Six sigma and process capability method. For this purpose, author used data processing software to obtain more accurate results. The software was used a combination of six sigma and process capability analysis. DMAIC method explained step by step process to describe and establish improvement.

- *Define*

In the Define phase, the project objective was to improve the energy efficiency of the power generation system by optimizing the steam-to-electricity ratio of the steam turbine. The baseline performance indicated a sub-optimal steam-to-electricity ratio compared to the target range based on the turbine performance curve as shown in Figure 5. This deviation signified potential inefficiencies in steam utilization and provided the foundation for problem identification.

The problem identified in this phase was the excessive steam consumption relative to power output, which indicated inefficiency in the performance of steam turbine. This issue led to higher energy costs and reduced overall plant efficiency, necessitating a structured improvement approach through the Six Sigma DMAIC methodology. Trend of excessive steam consumption has shown in Figure 1. *Measure*

This phase was aim to document and understand the current status of the steam and electricity distribution totalizer. All data using steam turbine operation in 2024 – 2025 period before improvement. The analysis of the steam-to-electricity ratio is one of the key parameters in evaluating the performance of a steam turbine-based power generation system. This ratio indicates the amount of steam consumption required to produce a certain amount of electrical energy. The lower the ratio value, then was more efficient the utilization of steam in the energy conversion process, reflecting better thermodynamic performance of the turbine. Conversely, a high ratio value may indicate potential inefficiencies either in the turbine's operating conditions or within its supporting systems.

Mathematically, this ratio can be expressed as follows (*Department of Engineering* PT. XYS):

$$R = \frac{m_{steam}}{P_{electricity}} \tag{1}$$

Where R is Steam-to-electricity ratio (kg/kWh), m_{steam} is Steam mass (kg), and $P_{electricity}$ is Generated electrical power (kWh). Table 3 show the ratio of steam consumption (steam distribution to steam turbine) day to day operation of steam turbine. Steam flow meter and kwh meter is used to record steam and electricity distribution amount.

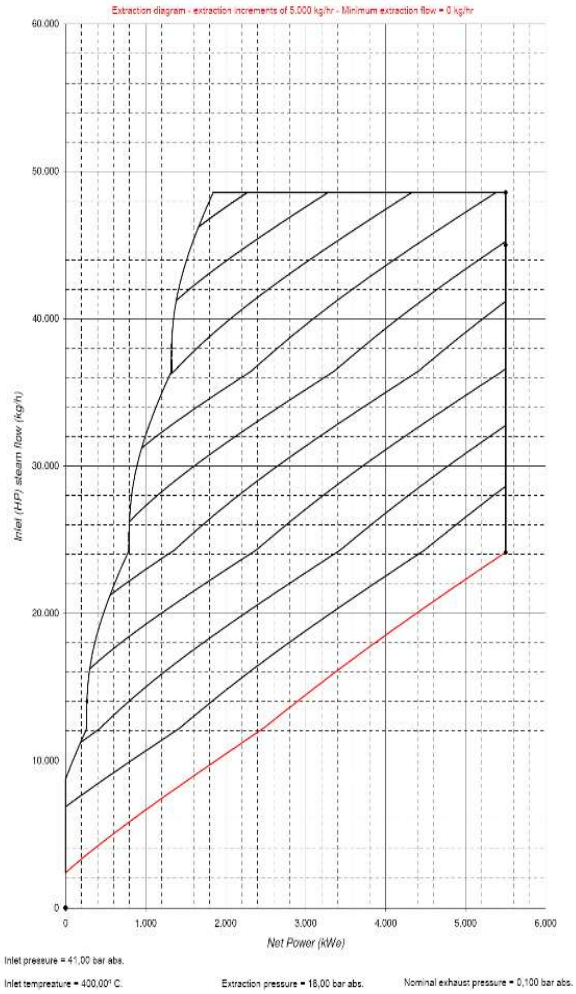

Figure 5: Performance Curve

- *Analyze*

In this stage, author used the histogram chart to evaluate whether the ratio of steam turbine in normal condition or out of parameter specification. Figure 6. Shown the histogram chart. Figure 7. Shown the capability analysis before improvement based on data in table 3. Process capability indicates that the current process performance is significantly below acceptable levels based on key capability metrics.

C_p or P_P (potential process capability) in figure 7 shows 0.30. This value represents the potential capability of the process assuming it is perfectly centered between the specification limits. A C_p value of 0.30 is far below the generally accepted industry standard of 1.33, indicating that the spread of the process variation is too wide relative to the allowable tolerance. In practical terms, even under ideal centering, the process cannot consistently meet customer specifications. C_{pk} or P_{Pk} (Actual process Capability) in Figure 7 show the data analysis of negative (-) 0.16. This metric was accounts for both process variation and the degree of centering between the specification limits. A negative C_{pk} value suggests that the process mean is not only off-center but actually falls outside the specifications limit. Specifically, below the lower specification limit (LSL). This indicates the process is producing a substantial number of nonconforming outputs and corrective action is urgently required.

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The other parameter, z bench value is negative (-) 0.40. Z bench measures the sigma level of the process from the mean to the closest specification limit. A z-bench of -0.40 reflects extremely poor process performance, with the process mean already lying outside the specification range. This corresponds to a defect rate of 562231 part per million (DPMP), which is far beyond acceptable levels in any quality-driven environment, and dramatically higher than six sigma standards of 3.4 DPMO.

Table 3: Steam and electricity ratio at steam turbine operation before improvement

Date	Steam and electricity ratio (kg/kwh)	Date	Steam and electricity ratio (kg/kwh)
1 Feb 2024	5.29	27 Apr 2024	5.29
2 Feb 2024	5.24	28 Apr 2024	5.19
3 Feb 2024	5.03	29 Apr 2024	5.29
4 Feb 2024	5.09	30 Apr 2024	5.12
5 Feb 2024	5.16	1 May 2024	5.21
6 Feb 2024	5.18	2 May 2024	5.25
7 Feb 2024	5.11	3 May 2024	5.24
8 Feb 2024	5.06	4 May 2024	5.27
9 Feb 2024	5.13	5 May 2024	5.40
10 Feb 2024	5.23	6 May 2024	5.29
11 Feb 2024	5.00	7 May 2024	5.35
12 Feb 2024	4.73	8 May 2024	5.28
13 Feb 2024	5.22	9 May 2024	5.25
16 Feb 2024	5.04	10 May 2024	5.22
17 Feb 2024	4.92	11 May 2024	5.33
18 Feb 2024	4.94	12 May 2024	5.34
19 Feb 2024	4.84	13 May 2024	5.38
20 Feb 2024	5.09	14 May 2024	5.38
21 Feb 2024	5.12	15 May 2024	5.32
9 Mar 2024	4.45	16 May 2024	5.46
10 Mar 2024	4.75	17 May 2024	4.97
13 Mar 2024	5.09	18 May 2024	5.06
16 Mar 2024	4.12	19 May 2024	5.29
17 Mar 2024	4.90	20 May 2024	4.66
18 Mar 2024	5.05	21 May 2024	4.65
19 Mar 2024	4.70	22 May 2024	5.07
20 Mar 2024	4.77	23 May 2024	4.99
21 Mar 2024	4.71	24 May 2024	5.06
22 Mar 2024	4.65	25 May 2024	5.00
25 Mar 2024	5.04	26 May 2024	5.26
26 Mar 2024	5.17	27 May 2024	5.38
27 Mar 2024	4.16	28 May 2024	5.09
28 Mar 2024	4.92	29 May 2024	5.16
29 Mar 2024	4.38	30 May 2024	5.13
30 Mar 2024	4.29	31 May 2024	5.19
31 Mar 2024	4.04	1 Jun 2024	5.29
1 Apr 2024	4.49	2 Jun 2024	5.23
2 Apr 2024	4.89	3 Jun 2024	5.36
3 Apr 2024	5.09	4 Jun 2024	5.32
4 Apr 2024	4.96	9 Jun 2024	5.38
5 Apr 2024	4.92	10 Jun 2024	5.32
6 Apr 2024	4.49	11 Jun 2024	5.44
7 Apr 2024	4.67	12 Jun 2024	5.42
20 Apr 2024	4.66	13 Jun 2024	5.36
21 Apr 2024	4.43	14 Jun 2024	5.18
22 Apr 2024	4.57	15 Jun 2024	5.19
23 Apr 2024	5.10	16 Jun 2024	5.36
24 Apr 2024	5.45	17 Jun 2024	5.26
25 Apr 2024	5.16	18 Jun 2024	4.90
26 Apr 2024	5.27	26 Jun 2024	5.46

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Figure 8 show the diagnostic report I-MR chart and normality plot test based on Anderson-Darling method. The diagnostic reports were presented in the Figure 8, evaluates the statistical stability and normality of the process before improvement, using an I-MR chart and a normality test.

I-MR (Individual-Moving Range) charts consist of two subplots. The upper chart displays the individual values of process measurements, while the lower chart shows the moving range between consecutive data points. Several data points in the individual values chart exceed the upper control limit (UCL), indication potential special causes of variation and suggesting that the process is not statistically stable. Similarly, the moving range chart reveals fluctuations beyond the control limits reinforcing the indication of inconsistent variation within the process. These patterns imply that the process lacks control and predictability, which compromises the reliability of any capability assessment based on this dataset.

In Figure 8 shown the normality of the data distribution was assessed using the Anderson-Darling test. The normality plot shows a significant deviation of the data points from reference line, particularly in the upper tail. The P value is less than 0.005, leading to a rejection of the null hypothesis that data follow a normal distribution. Therefore, the dataset does not meet the normality assumption, which a key requirement for traditional parametric capability induces such as Cp and Cpk.

A root cause investigation was carried out by using the fishbone diagram (Ishikawa) diagram. The diagram shown in Figure 9 illustrated all potential causes contribution to the high steam-electricity ratio. In Ishikawa diagram such as Man, machine, method, material, and environment represent the main cause framework used to identified the root cause of the problem or issue. Management, engineer, and executive operational gathered to discuss the identified root causes. Afterwards, all potential contributing factors were addressed and resolved one by one. Figure 9 show only Man, machine, method and material influence the high steam consumption for electricity generation. Utility team has investigated for all root cause, which is in fish bone diagram.

The process under evaluation is both statistically unstable and non-normally distributed. As a result, any capability analysis based on this data should be interpreted with caution. To ensure valid capability evaluation, it is necessary to first stabilize the process by identifying and eliminating sources of variation. The calculation of the process capability and the creation of the histogram diagram were performed using Minitab software.

- *Improve*

The initial investigation was conducted involving all personnel (man) responsible for data collection and machinery operation. The results of the investigation indicated no errors in either the steam and electricity data collection or the operation of the machinery.

Second, from the methodological perspective, no errors were found in the calculation of steam-to-electricity ratio. The quantities of steam and electricity were verified to be accurate. As the distribution values were matched with the consumption data reported by each plant user Third, the material used to drive the turbine rotor, which generates electricity, is steam.

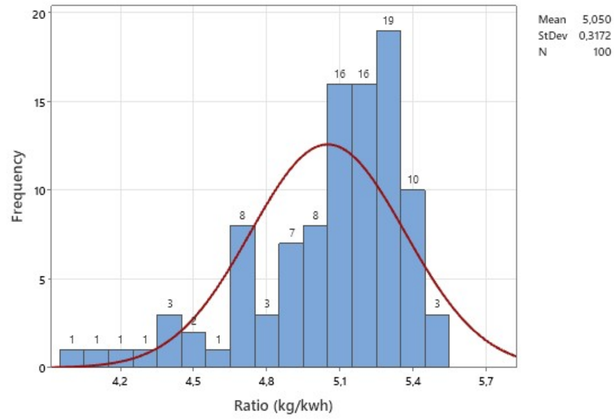

Figure 6: Histogram chart of ratio before improvement (kg/kwh)

Therefore, maintaining steam quality is necessary. Steam quality is closely related to boiler feedwater quality. In this case, the boiler water quality was within the acceptable range, and no issues related to steam quality were identified. According to standard procedures, when the turbine and boiler have been shut down for an extended period, steam blowing is performed prior to start-up to remove any impurities within the pipeline.

Fourth, from machine perspective, there are four aspects identified for further investigation: Steam leakage, chemical deposits on the rotor, low vacuum level, and power generation performance. The investigation concluded that the primary issue is the low vacuum level. A leak was found in the turbine condenser, which affected the rotor speed. The leak in condenser ducting was detected by filling the condenser section with colored water. The presence of leakage was indicated by dripping or visible traces of water escaping from several areas of the condenser. The condenser in a steam turbine operates by creating a very low pressure (vacuum) at the turbine exhaust. Its purposes are to: reduce the final pressure of steam expansion, maximize the amount of work extracted from the steam, and improve thermal efficiency of the system.

Leakage in the condenser allows outside air or non-condensable gasses to enter the system, as a result: the pressure inside the condenser increases (vacuum decreases), the pressure differential between the turbine inlet and exhaust is reduced, the turbine loses part of its ability to expanded steam effectively. This leakage led to an increase in steam consumption by the turbine. The issue was resolved by repairing the leak through argon welding.

- *Control*

At this point, to ensure the sustainability of improvements and maintain optimal performance, a control plan has been implemented to regularly monitor the steam to electricity ratio (kg/kwh) on a daily basis.

Based on the data collected from 27 June 2024 to 25 June 2025 on table 4, the values have generally remained within the expected operating range, indicating that the process remains stable post-improvement. There were several days without recorded data due to turbine shutdowns. During these periods, the plant was supplied with electricity from the national grid (PLN). Daily monitoring allows for immediate

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corrective action if abnormal trends or outliers are observed. The team has assigned responsible personnel to continue tracking performance, verify standard operating procedures (SOP) adherence, and respond to any future deviations.

4.0 RESULT AND DISCUSSION

4.1 Operational Implications of Initial Process before Improvement

Before implementation of process improvement through the six-sigma approach, the system under observation exhibited characteristics of statistical instability and non-normal distribution. This instability was evident from data fluctuations that exceeded the control limits indicating the presence of special cause variation. Additionally, the deviation from a normal distribution suggested that conventional process capability metrics, such as C_p and C_{pk}, might not accurately reflect the actual process performance.

In Figure 8, the DPMO value before improvement is 563231, and Cp (or potential process capability, Pp) value of 0.30, indicating the process's potential performance assuming it is perfectly centered within the specification limits. However, a Cp of 0.30 is significantly lower than the commonly accepted benchmark of 1.33, suggesting that the process variation is excessively wide compared to the allowable tolerance range. In essence, even with ideal centering, the process would still be unable to consistently satisfy customer requirements.

The C_{pk} (or actual process capability, P_{pk}) value shown in data before improvement is -0.16, reflecting both process variability and how well the process mean aligns with the specification limits. A negative C_{pk} value indicates that the process means lies outside the specification range. Specifically, below the lower specification limit (LSL). This demonstrates that the process is generating a large proportion of nonconforming products, and immediate corrective measures are necessary.

Operationally, this condition leads to a decrease in steam production efficiency, an increase in operational costs, and a reduction in system reliability. High process variation and frequent nonconformance result in elevated levels of reworks and energy losses, as well as excessive use oof critical resources, including fuel, and water. In steam generation systems, such inefficiencies may manifest in the form of inconsistent steam pressure, unstable temperature profiles, poor heat transfer efficiency or frequent boiler trips, which ultimately disrupt downstream operations and energy supply reliability. Moreover, uncertainty in steam quality or availability poses a risk to critical processes, can lead to customer dissatisfaction.

In this context, the DMAIC (Define, Measure, Analyze, Improve, Control) methodology becomes essential as a structured improvement framework. Through its systematic stages, the root causes of process variation such as fluctuating feedwater temperature, burner misalignment, or improper control loop tuning can be identified and effectively addressed. This allows the steam production process to be normalized, stabilized, and enhanced in terms of capability. Ultimately, the implementation of DMAIC not only improves technical process performance, such as better combustion efficiency and reduced steam losses, but also delivers tangible business value through cost efficiency, enhanced operational reliability, and greater customer satisfaction.

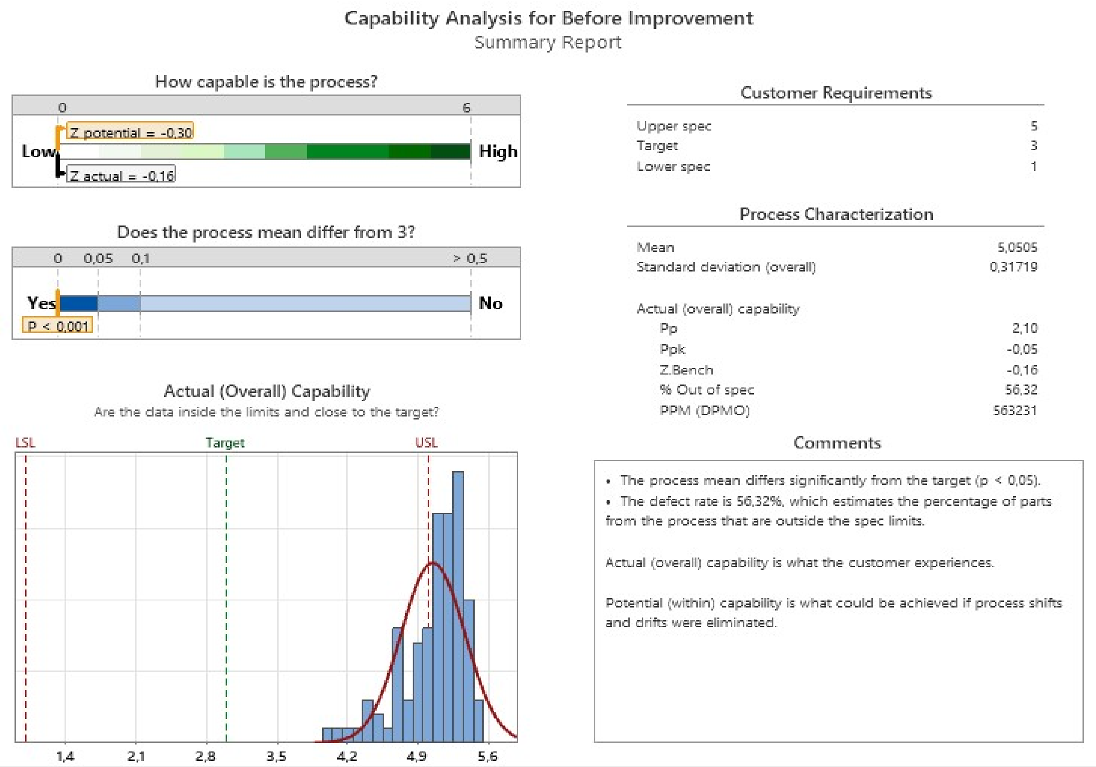

Figure 7: Capability nalysis before improvement

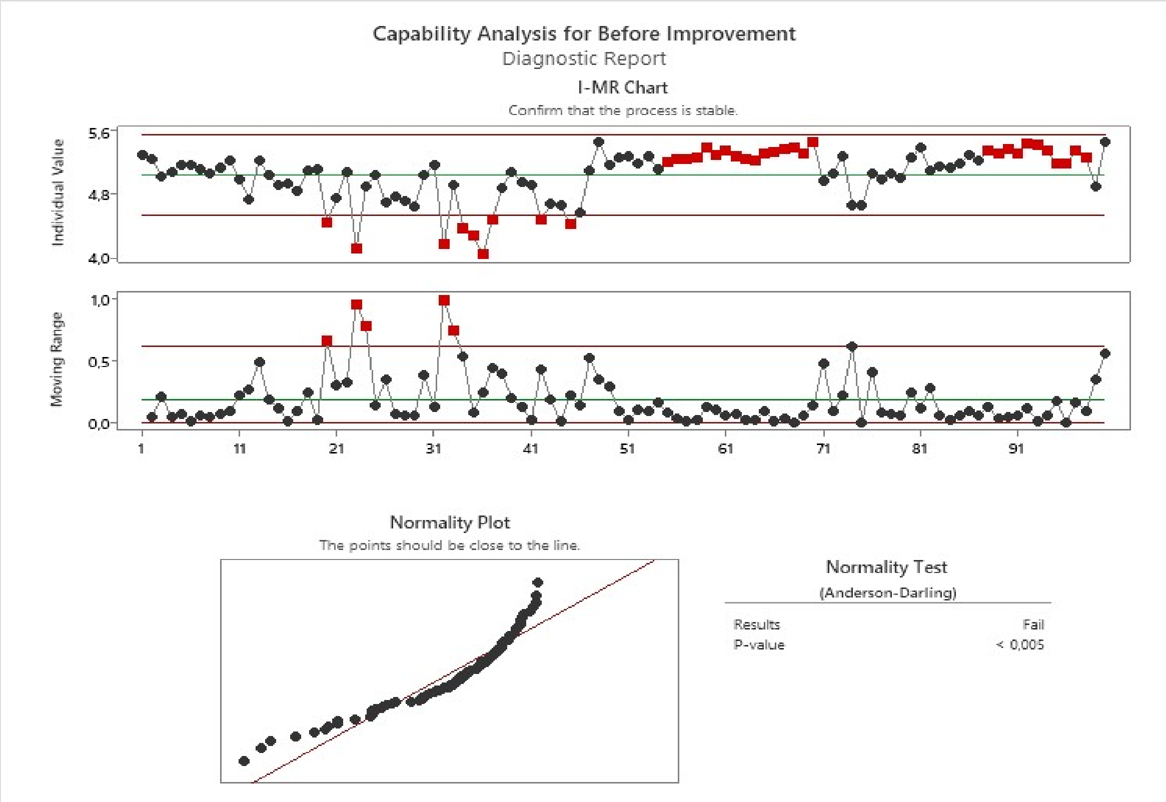

Figure 8: Diagnostic report: Process stability and normality assessment before improvement

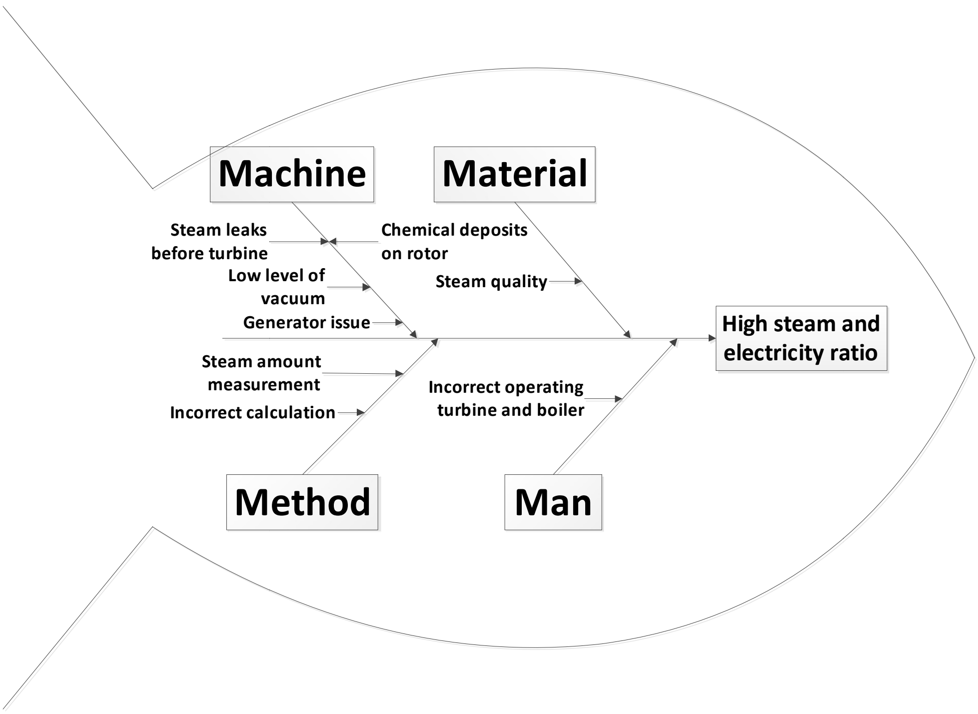

Figure 9: Fishbone (Ishikawa diagram) of high steam and electricity ratio

4.2 Capability Process Analysis after Improvement

After all data were collected as shown in Table 4, a process capability analysis was conducted, including the calculation of C_p, C_{pk}, and Z-bench (sigma level). In Figure 10, the DPMO value decreases to 1143, and the Cp (Potential Process Capability) shows a value of 1.39. This value represents the potential capability of the process assuming it is perfectly centered between the specification limits. A Cp value of 1.39 is above the generally accepted industry benchmark of 1.33, indicating that the process variation (spread) is acceptable, and under ideal conditions (perfect centering), the process is capable of meeting customer requirements consistently.

Table 4: Steam and electricity ratio at steam turbine operation after improvement

Date	Steam and electricity ratio (kg/kwh)	Date	Steam and electricity ratio (kg/kwh)
27 Jun 2024	3.34	27 Aug 2024	4.38
28 Jun 2024	3.68	28 Aug 2024	3.64
29 Jun 2024	2.79	29 Aug 2024	4.43
30 Jun 2024	3.04	10 Sep 2024	3.41
1 Jul 2024	2.68	11 Sep 2024	3.09
2 Jul 2024	3.27	12 Sep 2024	3.18
3 Jul 2024	4.45	14 Sep 2024	3.97
4 Jul 2024	3.02	15 Sep 2024	4.00
5 Jul 2024	3.04	16 Sep 2024	3.85
6 Jul 2024	2.83	17 Sep 2024	4.24
7 Jul 2024	2.83	18 Sep 2024	3.87
8 Jul 2024	3.39	19 Apr 2025	2.45
9 Jul 2024	3.11	20 Apr 2025	4.14
10 Jul 2024	3.26	21 Apr 2025	3.64
11 Jul 2024	3.56	22 Apr 2025	3.79
12 Jul 2024	2.41	23 Apr 2025	3.33
13 Jul 2024	3.98	24 Apr 2025	2.94
14 Jul 2024	3.24	25 Apr 2025	2.92
15 Jul 2024	4.18	26 Apr 2025	3.99
16 Jul 2024	3.79	27 Apr 2025	3.09
17 Jul 2024	3.71	28 Apr 2025	3.12
18 Jul 2024	3.20	29 Apr 2025	3.74
19 Jul 2024	4.05	30 Apr 2025	3.37
20 Jul 2024	4.27	1 May 2025	3.29
21 Jul 2024	4.18	2 May 2025	3.92
22 Jul 2024	3.97	21 May 2025	3.55
23 Jul 2024	4.21	22 May 2025	3.49
24 Jul 2024	3.93	23 May 2025	3.65
30 Jul 2024	3.64	24 May 2025	3.05
31 Jul 2024	4.37	25 May 2025	3.81
1 Aug 2024	3.75	26 May 2025	3.66
2 Aug 2024	4.52	27 May 2025	3.90
3 Aug 2024	3.74	7 Jun 2025	3.22
4 Aug 2024	3.51	8 Jun 2025	3.28
5 Aug 2024	4.40	9 Jun 2025	3.72
6 Aug 2024	4.13	10 Jun 2025	3.48
10 Aug 2024	3.09	11 Jun 2025	3.53
11 Aug 2024	3.56	12 Jun 2025	3.29
12 Aug 2024	3.13	13 Jun 2025	3.52
13 Aug 2024	3.65	14 Jun 2025	3.44
14 Aug 2024	3.06	15 Jun 2025	3.52
15 Aug 2024	3.15	16 Jun 2025	3.41
16 Aug 2024	3.87	18 Jun 2025	3.35
19 Aug 2024	4.20	19 Jun 2025	2.70
20 Aug 2024	3.65	20 Jun 2025	3.00
21 Aug 2024	3.35	21 Jun 2025	2.96
22 Aug 2024	3.39	22 Jun 2025	3.01
23 Aug 2024	3.66	23 Jun 2025	3.07
25 Aug 2024	4.13	24 Jun 2025	2.93
26 Aug 2024	4.21	25 Jun 2025	3.71

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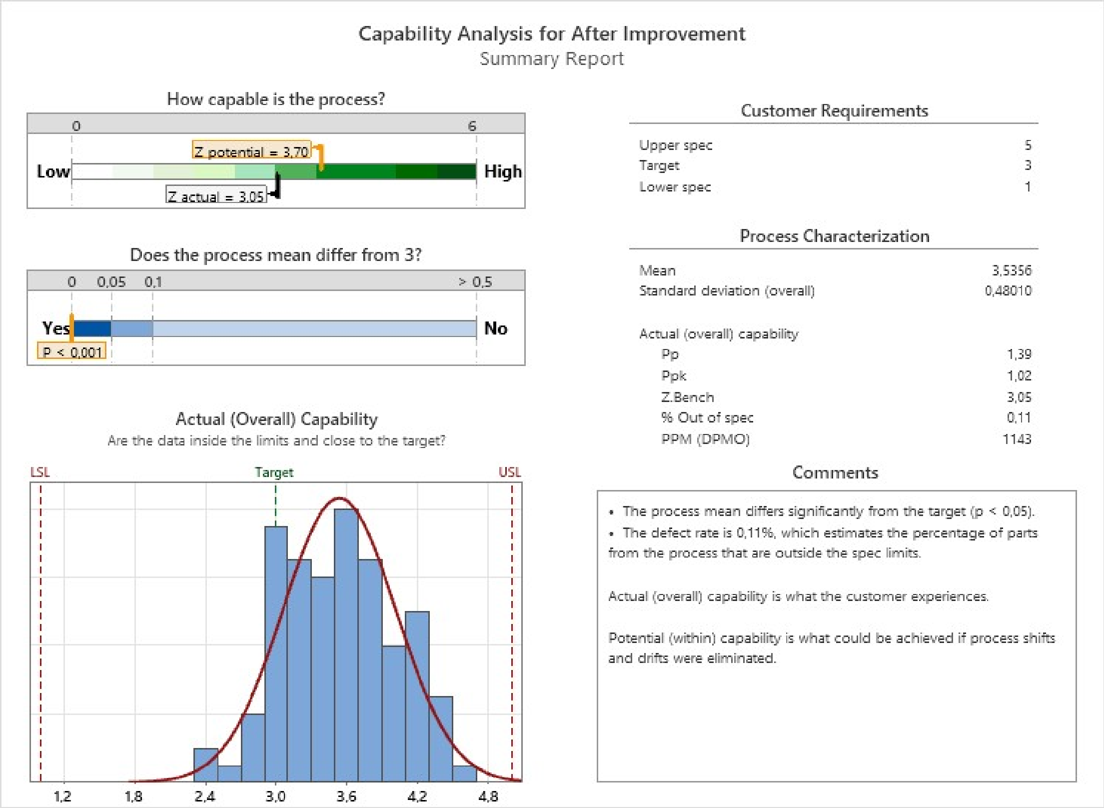

Figure 10: Capability analysis after improvement

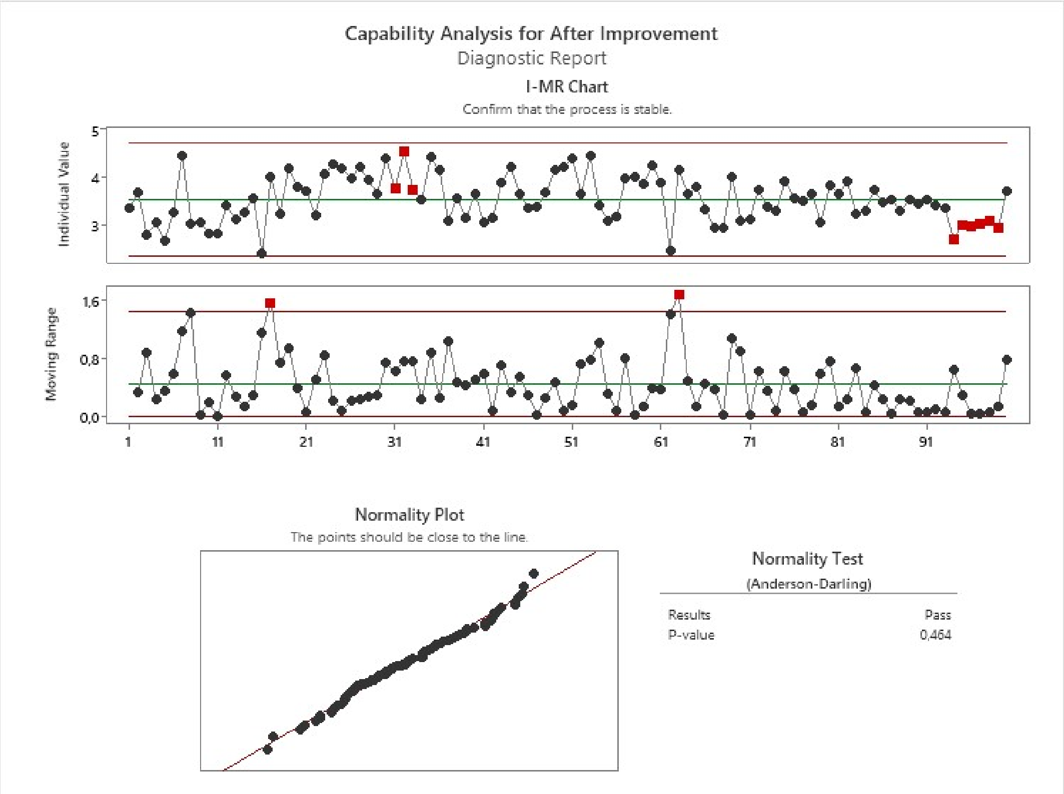

Figure 11. Diagnostic Report: Process stability and normality assessment after improvement

The C_{pk} (actual process capability) in the Figure 11 shows a value of 1.02. This matric account for both the process variation and the degree of centering between the specification limits. Although it is lower than C_p, a C_{pk} of 1.02 still suggest a marginally capable process, but indicates that the process mean is not perfectly centered and is slightly shifted from the target. This misalignment results in some outputs being closer to the specification limits, increasing the risk of nonconformance compared to a perfectly centered process.

The Z-bench value is shown as 3.05, which corresponds to a sigma level of 3.05. This value reflects a reasonably capable process, with a defect rate of only 0.11% or 1143 defects per million opportunities (DPMO). Although this is a significant improvement a much better than typical industry standards, it still falls short of six sigma performance levels (3.4 DPMO). Nonetheless, the process is how capable of meeting specification with relatively low probability of producing defects.

Figure 11 presents the diagnostic report consisting of an I-MR chart and a normality plot based on the Anderson-Darling test. his analysis aims to assess whether the process, after the implemented improvements, demonstrates adequate statistical control and distributional conformity.

The I-MR chart is divided into two components. The individual chart (top) illustrates the variation in daily steam-to-electricity ratio, while the moving range chart (bottom) displays the consecutive measurements. Although the majority of data points remain within control limits, several instances (highlighted by red points) indicate violations of control rules, suggesting that special causes of variation may still influencing the process.

These exceptions, particularly clusters above upper control limit, signal that the process, despite improvements, is not yet fully stable. The fluctuations observed in the moving range chart further support this conclusion, showing intermittent inconsistencies in process variability.

The normality of the data was evaluated using th Anderson-darling test, with a resulting p-value of 0.464. since this value exceeds the commonly accepted threshold of 0.05, the data follows a normal distribution. This is visually confirmed by the normality plot, where the points largely align with the reference line (an indication that distributional assumptions for capability analysis are satisfied).

5.0 CONCLUSION

In conclusion, the integration of the Six Sigma DMAIC methodology with process capability analysis effectively enhanced the operational performance of the in-house power generation system by significantly reducing the steam-to-electricity ratio, improving energy efficiency, and reducing energy consumption. It is also important to note that several red points on the control chart in Figure 11, although visually within the control limits, were flagged by Minitab based on Western Electric or Nelson rules. These rules detect potential special-cause variations, such as sustained runs of data on one side of the mean, trending behavior, or clustering near control limits, which may indicate process shifts or abnormal operating patterns. Therefore, while the overall process remains largely stable, these signals warrant closer monitoring to prevent potential deviations from reoccurring.

For future work, more specific efforts should be directed toward addressing the unique challenges of refinery-captive power plant systems. This includes implementing advanced root caused analysis tools like FMEA focused on common issues such as steam leakage, boiler fouling, and condensate loss. Integrating predictive analytics or machine learning models to forecast turbine efficiency degradation and boiler performance decline could enhance proactive maintenance. Expanding Six Sigma applications to auxiliary systems, such as boiler feed water treatment and condensate recovery, would also improve overall plant reliability. Furthermore, incorporating a detailed cost–benefit analysis would strengthen the linkage between technical improvements and their economic impact, ensuring data-driven decisions that maximize both efficiency and sustainability.

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